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Multiple Enrollment for Fingerprint Recognition: State of the Art Survey

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Abstract— **Fingerprints are the oldest biometrics and have received vast research attention compared to other biometrics. In this survey, the viability of fingerprint as a biometric is established and an account of the technological development in multiple enrollment for fingerprint recognition is provided. A total number of 55 papers representing the state of the art in multiple enrollment for fingerprint recognition before 2004 and until up-to-date, are examined and presented in this survey with respect to approach methodology and experimentation results. Comparisons in terms of recognition accuracy among different approaches are given, challenges analyzed and recommendations made. An overall analysis of the survey is done together with the challenges identified and a way forward drawn. Finally, a list of laboratories working on multiple enrollment for fingerprint recognition is attached. This survey serves as a quick overview of the state of the art in multiple enrollment for fingerprint recognition for the past two decades.**

Keywords- Multiple enrollment, Recognition Performance, State of the art survey, minutiae-based matching, pattern-based matching.

I. INTRODUCTION: FINGERPRINT RECOGNITION

In this section, an account of the fingerprint characteristics that establish its viability as a biometric is presented, and the concept of Multiple Enrollment for fingerprint recognition discussed. A brief survey on the technologies or approaches developed for Multiple Enrollment for fingerprint recognition before 2004 is conducted, paving way for a more extensive survey on the state of the art development from the year 2004 onwards.

A biometric system is an electronic implementation of automatic human recognition using body characteristics, such as ear, vein, DNA, face, fingerprint, iris, gaits and voice, which are collectively called biometric. The current demand for higher security and more convenient operations, for example in the cases of access control and personal data protection, has spurred intensive research, deployment and commercialization of biometric systems. Distinct from traditional identification methods, which rely on what you know (e.g. PIN, Password) or what you have (e.g. key, token), a biometric system makes judgment based only on what you are, and thus meets more stringent security requirement, while relieving users from the burden of remembering passwords[1].

The use of fingerprints is evident in the field of forensics, fingerprint recognition has been (can be) important in corpse and terrorist identification, criminal investigation, parenthood determination etc. Its application is also evident in the government and commercial sectors most especially in the national identification cards, drivers' license, social security, boarder and passport control, computer network logon, ATMs and credit cards, physical access control, etc., [1], [6], [7], [8] to mention but a few. Fingerprint recognition has not only acquired a wide spread use but also triggers security concerns in terms of errors and its recognition performance.

A fingerprint has qualities that enable it to become a biometric. From an anatomical perspective, the fingerprint is composed of a pattern of ridge lines and valleys. These are represented by dark and bright lines respectively as illustrated in Fig 1. Furthermore, the ridge lines consist of other components called sweat pores. On the other hand, as the ridge patterns flow along the finger, (i) terminations can occur whereby the ridge curve simply ends or (ii) bifurcations can occur; whereby the ridge line path divides into two paths. It is these terminations and bifurcations (illustrated in Fig 1) of the ridge lines that make it possible to locate distinctive features called minutiae points [9], which are very important in the fingerprint matching exercise. The other features a fingerprint possess are (i) the whorl and arc as classified by Lee and Gaensslen in [11]; and (ii) the loop and delta; which are squares and tringles that work as regulator points where the ridge lines are enfolded [10].

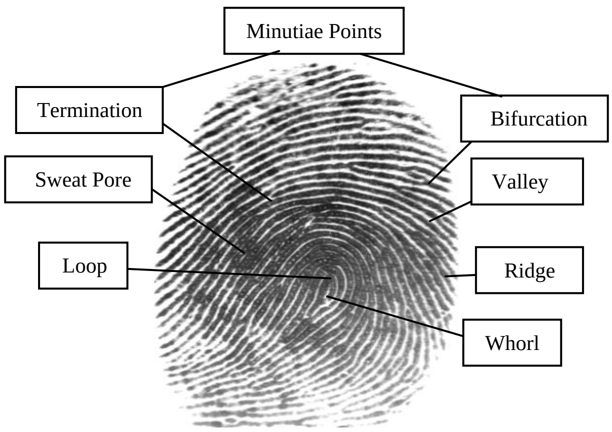

Fig. 1 Anatomy of the Fingerprint (Extracted from FVC2004 DB1 [46])

The deep complex structure and vast number of unique features gives rise to a wide variation of fingerprints among individuals; this guarantees sufficient differentiating capability of fingerprints in identifying people and impedance against spooling attempt. In addition, biometric research [1], [2] reports that the use of fingerprints as a biometric characteristic is one of the oldest and widely used method for recognition because of their high distinctiveness, high permanence, and high performance. The universality, distinctiveness, invariance to age, collect-ability and acceptability also jointly establish the candidacy of fingerprints as a biometric.

1.1. Multiple Enrollment for Fingerprint Recognition in a Nut Shell

Acquiring accurate fingerprint images for recognition in a onetime capture is infeasible because not all the necessary and distinguishable fingerprint information may be collected. This can be due to a number of factors such as noise, errors in the feature extraction module, fingerprint displacement and rotation during the enrollment or capture stage, distortion, low quality fingerprint images, worn-out fingerprint images, partial overlap, finger pressure and skin condition [1], [5]; these decrease the recognition performance/accuracy and make it hard to relay on single enrollment where one fingerprint sample is collected per individual.

Enrollment of individuals using multiple fingerprint samples (multiple enrollment) is a known solution that can help in extending the information of a single enrolled fingerprint image and also ensure the reliability of each fingerprint image [1]. Multiple enrollment can also improve the recognition accuracy of the fingerprint recognition system by lowering the error rates, allowing robustness by lowering the False Rejection Rates for low quality or worn-out fingerprint images and also make spoofing harder [1]. In multiple enrollment, the multiple fingerprint samples per individual can be collected in one session (with in the same period of time and day) or at multiple sessions for example after a difference of about two weeks' time or more. Multiple samples of the same finger or different fingers can be collected for enrollment, stored as templates and later used for verification during matching.

1.2. A brief survey on the technologies/approaches developed for Multiple Enrollment for Fingerprint Recognition before 2004

The viability of the fingerprint as a biometric is also well demonstrated by practical applications. Historically, fingerprint, as a measure to distinguish individuals, was introduced as early as 1788 by Mayer [9]; where the anatomy of a fingerprint was described and a number of unique features acknowledged and characterized. However, the popularity of fingerprint was obscured until the ground breaking discovery of the uniqueness of fingerprint in 1880 by Henry Fauld [1], which, given the available technologies at that time, provided unparalleled accuracy. Since then, developments and improvements in the fingerprint field continued; for example, in 1888 where Galton [12] realized minutiae as other very important features for differentiating individual fingerprints. In 1899, Edward Henry also introduced the so called Henry system which was to classify fingerprints of different individuals [11]. For all that time, fingerprint had not been formally permitted as a valid personal identification not until the beginning of the twentieth century when it was approved and also included among the forensics analysis routine standards [11]. It is from the 1960s to 1969 when fingerprint identification began to transfer to automation and it's the same period when the Federal Bureau of Investigation fronted the idea of automating the fingerprint identification process. From the 1970s to the 1980s, fingerprint scanners for automation and technologies for digitization, image compression, image quality and classification, feature (minutiae) extraction and matching techniques were developed. From the 1980s onwards, advancements in fingerprint technology were seen. It is within this period when the so called M40 algorithm for FBI became operational. Not only that but also five Automated Fingerprint Identification Systems (AFIS) were deployed, another Integrated Automated Fingerprint Identification Systems (IAFIS) developed and made operational by 1999. Technology advancements in fingerprint identification continued until 2003 when the Fingerprint Vendor Technology Evaluation was instigated to evaluate how accurate fingerprint recognition systems were [32].

In the twentieth century, a lot of research was conducted in the field of fingerprint recognition and it is when the technologies such as fingerprint classification, latent fingerprint acquisition, and fingerprint comparison were established [1]. At the same time, criminal fingerprint databases and investigation agencies (such as the FBI fingerprint identification division) were established [11]. It was within the same century that the current popular Automatic fingerprint recognition technology was established [1]

As time went by, new techniques were introduced to improve performance in fingerprint recognition systems. The fusion method of combining multiple biometric traits, or multiple instances of the same biometric trait, or complementary feature extraction and matching algorithms for the same instance of a biometric trait, was introduced to improve performance/accuracy in huge/sizable automatic identification systems [1]. With fingerprints, the fusion approach can take on five forms; (i) Combining other biometric characteristics like ear, iris, or face with fingerprints (multiple traits) [37], (ii) Combining multiple fingers (e.g. 2 0r 3 fingers) of the same person [35], (iii) combining multiple samples of the same finger (fingerprint information) acquired after using different sensors [1], (iv) combining multiple samples of the same finger [36]; where we have multiple enrolled fingerprint samples combined and (v) combining multiple representations and matching algorithms [38]; where diverse approaches to feature extraction and/or matching of fingerprints are combined.

Added to the above are other techniques that have been used/applied to further achieve better performance while using multiple enrollment in fingerprint recognition systems. First is the image level fusion technique which is mainly used when combining multiple images of the same finger. Second is the feature level fusion technique which is mostly used when combining multiple feature sets coming from the same finger. Third is the rank level fusion technique which is commonly used in identification systems to rank candidates in a templates database after a matching has been done. Fourth is the Score level fusion technique, which has commonly been used by many researchers due to its ability to combine information from all the sources as presented in the paragraph above. Last is the decision level technique which is mainly used to provide a final match decision. It also combines information from all sources as presented in the paragraph above. Our analysis shows that although it is possible to fuse multiple fingers at all the levels mentioned above, fusion at score level has been the most popularly used [13], [14] implementation level for multi-finger recognition systems.

Research Studies from the late 90s; 1995 [15], 1997 [16], 1998 [17], [40], 1999 [18], [42], 2000 [48], 2001 [37], 2002 [38] and in 2003 [19], [20], [50], [54] have shown that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used. This survey mainly focuses on fusion using information from multiple fingers [35] of the same person; since it is one of the most commonly used and recommended for medium to large-scale automatic identification systems [1]. However, fusion using information from multiple samples of the same finger is also addressed in the survey, since multiple enrollment is also deployed.

Developments in multiple enrollment (with multiple fingers [35]) for fingerprint recognition started way back in the 20th century being evident in huge automatic identification systems like border control, law enforcement, background checks, voter registration system and many others. This approach was mainly introduced to improve recognition accuracy. This would not only improve performance but also balance cost, information content (by adding on to the little identification information from single fingers and single enrollment) and acquisition throughputs in large-scale automatic identification applications [1]. A number of researchers have reported that when two or more fingers of the same individual are joined, there is a great improvement in recognition accuracy. An example is the FVC2000 Fingerprint Verification Competition [5] where up to four fingers were collected from each person; taking the forefinger and middle finger of both hands in the order, first sample of left forefinger, first sample of right forefinger, first sample of left middle finger, first sample of right middle finger, second sample of left forefinger, second sample of right forefinger . . . , etc., up to 8 samples per person. Huge performance improvements were realized by the different researchers in the competition.

Prabhakar and Jain [21] in 2001/2002 showed that if different fingerprint matching algorithms are combined (four algorithms were used), the overall performance would be increased. Not only that, but they also showed that combining multiple impressions or multiple fingers greatly improved the verification performance of the fingerprint recognition system. They carried out multiple enrollment by combining two fingerprint samples of the same finger or different fingers to verify the effectiveness of their proposed scheme. Their experiments were carried out on a database of 167 individuals (four impressions for each four fingers, 167x4x4 producing 2672 fingerprints) using minutiae-based matching and filter-based matching together with decision level fusion. Their results show that when multiple impressions or multiple fingers were combined, the recognition accuracy improved by more than 4% and 5%. The EER obtained after combination was 1.4%.

In 2003, Simon-Zorita et al [34] further supplemented the idea of Prabhakar and Jain [21] by proposing the storage of three fingerprint samples of the same finger at the time of enrollment. Verification would then follow by comparing the reference fingerprint sample with all the three stored multiple enrollment samples and choosing the maximum score to be the fusion score. A greater improvement in recognition performance was achieved.

To improve performance and robustness of a fingerprint matcher, in 2003, Luca and Fabio in [28] provided a perceptron based fusion technique whereby after enrollment, matching takes place with the help of multiple fingerprint matchers, which then generate a set of the multiple verification scores. It is these multiple scores that are input to the perceptron which later fuses them to have a maximum separation between the genuine users and the impostors. They used the FVC2000-DB1 containing 800fingerprint images. Minutiae based matching was performed and a great improvement in recognition accuracy was observed with EERs of 1.2%, 1.5% and 3.3% for experiments a, b and c respectively. The 2003 FpVTE 2003 fingerprint algorithm benchmarking activity carried out by the National Institute of Standards and Technology (NIST) also reported that when more fingers of an individual were combined, the recognition accuracy greatly improved [22].

The remaining part of this paper is structured as follows: In section 2, we provide some terminologies used in the field, how we categorized the different multiple enrollment matching techniques and the paper surveys. Section 3 discusses Summary of performance overview, a comparative assessment of the different approaches surveyed, the challenges identified and recommendations. Section 4 provides an overall analysis of the survey, the research gaps and way forward. Section 5 concludes the paper while the last section provides the references and list of labs working on multiple enrollment for fingerprint recognition

II. TERMINOLOGY, CATEGORIZATION & CLASSIFICATION, AND THE PAPER SURVEYS

In this section, we identified the different categories of papers published under multiple enrollment for fingerprint recognition, mostly from 2004 onwards. We consider this list exhaustive enough to make a comprehensive survey in the research area. We have also managed to categorize and classify the different papers under multiple enrollment for fingerprint recognition in four different ways; the matching technique used (Pattern-based Matching technique or Minutiae-based Matching technique), the size of dataset(s) on which the experiments were done, the execution time (aka speed) and memory used, as well as the performance/recognition accuracy that was achieved.

2.1 TERMINOLOGY

The following are some of the different terminologies under multiple enrollment for fingerprint recognition and as used in the survey and other sections that follow. We therefore recommend the readers to read the terminologies or else the information in the next sections may require you to always refer to the terminologies.

TABLE I: TERMINOLOGIES AND THEIR DESCRIPTIONS

Terminology	Description
AAD	Average Absolute Deviation
AFIS	Automated Fingerprint Identification Systems
IAFIS	Integrated Automated Fingerprint Identification Systems
ATM	Automated Teller Machine
PIN	Personal Identification Number
FBI	Federal Bureau of Investigation
FVC	Fingerprint Verification Competition
EER	Equal Error Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
FpVTE	Fingerprint Vender Technology Evaluation
NIST	National Institute of Standards and Technology
DB1	Database One
DB2	Database Two
DB3	Database Three
ms	millisecond

2.1 CATEGORIZATION AND CLASSIFICATION

Our multiple enrollment for fingerprint recognition: state of the art survey is categorized based on two ways; (i) the pattern-based matching technique presented in [2, 3, 4] and (ii) the minutiae-based matching technique discussed in [1]. These techniques were chosen for categorization and classification in this survey because of their popular use [1, 4]. The classification was done basing on four key areas; the matching technique used (Pattern-based Matching technique or Minutiae-based Matching technique), the size of dataset(s) on which the experiment were done, the execution time (aka speed) and memory used, as well as the performance/ recognition accuracy that was attained.

2.2 THE PAPER SURVEYS

2.2.1 MINUTIAE-BASED MATCHING TECHNIQUES

In the minutiae-based matching techniques, what happens is that after acquiring the fingerprint image sample, minutiae are extracted, stored as sets of points in a two dimensional plane and matching follows by determining the alignment between the template and the input minutiae sets which yield in the uttermost number of minutiae pairings. In our analysis, we have found the minutiae-based matching techniques known to be the most common and widely used fingerprint matching method [1, 4].

In 2004, the hybrid biometric systems like one in [55] which used the face and fingerprint as primary traits together with gender, ethnicity, and height as the soft characteristics, also showed a significant recognition performance improvement. Luca and Fabio in their 2004 research [29] fused multiple fingerprint sensors (optical and capacitive sensors) for fingerprint verification. Each sensor was subjected to fingers whose fingerprint images were captured; processed and distinguishable features (minutiae) extracted. The extracted feature sets were matched and two matching scores (each resulting from each sensor) are generated. It is these two scores that were combined to acquire a fused matching score. To attain a final decision, this score value would be evaluated based on a certain acceptance threshold, and a claimed identity would be accepted (as a genuine user) or rejected (as an impostor) if the score was above or below that acceptance threshold, respectively. A database of 20 individuals (with 1200 images) was used. A great recognition performance improvement of EER 2.2% was achieved after combining optical and capacitive matchers and using the Logstic-FD fusion rule. Other research Studies which show that a better recognition performance is attained when fusion of multiple sources of information is used than when a single source is used were in 2004 [49], 2007 [47], 2012 [53] and 2013 [51]

In their 2004 research, Ushmaev and Novikov [23] also report a great improvement in the recognition accuracy after using fingerprint data from multiple fingers. In the same year 2004, Lee, Choi, Lee and Kim [24] also report an improvement in the recognition accuracy after combining fingerprint data from two fingers. A database of 63 individuals (with each 20 fingerprint samples yielding 1260 total fingerprints) was used. Minutiae-based matching was carried out and score level fusion used to generate the final result. Wayman in 2004 [25] also carried out an evaluative research on the usage of fingerprint data coming from two or more fingers of an individual and a great recognition performance improvement was realized.

Umut, Ross and Jain [30] provide an automated template selection methodology that performs clustering to pick a template set which best characterizes the variability and typicality amongst the stored multiple fingerprint images. During the clustering process, a dendrogram which is in form of a binary tree whose nodes form clusters (representing fingerprint impressions), is outputted. It is from these clusters that the fingerprint samples with the minimum average distance from the other fingerprint samples are selected. Furthermore, the fingerprint samples are categorized basing on their average distance score in relation to other fingerprint samples and selection of those samples that display supreme likeness (those with the smallest average distance score) with all the other fingerprint impressions is done. With this technique, selection and ranking are based on Average Distance from the other impressions and then choose impressions with least average distance and uses minutiae as the fingerprint matching distinguishing feature. The experiments were carried out on a database of 50 different fingers with 200 impressions per finger an improvement in recognition performance was observed. EERs of 7.37% and 6.31% were obtained for the DEND method and MDIST method respectively.

The second NIST fingerprint algorithm benchmarking activity (NIST Proprietary Fingerprint Template (PTE) Testing) in 2005, also reported a rise in recognition accuracy when number of fingers were increased [26]. In their 2005 Study on Multi-unit Fingerprint Verification [27], Lee and colleagues also reported that the recognition accuracy was improved when fingerprint data from two fingerprints was used.

Chunyu and Zhou in 2006 carried out a comparative study of combining multiple enrolled samples for fingerprint verification [41]. Many schemes were studied which showed that there was always a greater recognition performance improvement when multiple enrollment was applied. They further proposed their own scheme which combined feature and decision fusion levels while using multiple impressions to obtain a far much better recognition performance. Minutiae-based matching was done and the databases used for the experiments were; THU (with 827 fingers and 8 impressions per finger yielding 6616 fingerprints), FVC2002 DB1 and FVC2002 DB2 [45]. A greater overall performance improvement in terms of FRR (0.0907) and FAR (7.97e-5) was observed with the proposed combination scheme.

In 2007 Lifeng Sha et al. [43] proposed a two-stage fusion scheme which uses multiple fingerprint impressions. They use a 2D wrapping model to transform all the multiple impressions and carry out a minutiae-based matching of the template fingerprint image with the reference fingerprint image. They use score level or decision level fusion to fuse the resulting scores from the different impressions to get a final result. All experiments were carried out on FVC2002 [45] database and a great improvement in recognition accuracy was achieved.

In 2009, Chunxiao, Yin, Jun, and Yang [31] in their research proposed a method that implements score level fusion using multiple fingerprint impressions for fingerprint verification to improve performance. Multiple samples of the same user's finger are enrolled and stored as templates for future reference. At the time of verification, the distance from the test fingerprint (claimed identity) and the centroid of reference fingerprints (stored templates) is computed in a multidimensional space. For comparability and matching, they measure the centroid of all the vertices for a given polyhedron and those vertices that are closer to the centre of the polyhedron are said to match better than all the others. The minutiae-based matching method is used to compare the reference fingerprint image and the stored template images and the distance output is later considered as the final score level fusion result. The FVC2000 DB1, FVC2000 DB2, FVC2002 DB2 and FVC2002 DB3 databases (of 100 individuals each with 8 impressions) [45] where used. Their results show a greater recognition accuracy is achieved when multiple enrollment with fusion was applied than in the uni-matcher. Equal Error Rates (EER) of 2.25%, and 5.75%, where obtained respectively.

To improve on recognition accuracy and reduce classification errors in biometric systems, Andres and Peter [39] in 2009 combined multiple instances of the same biometric, that is fingerprint and Eigenfinger and compare with the single instances. Minutiae and Eigenfinger features are extracted and stored as templates for future reference. For minutiae, matching of the stored templates then follows by a pair-wise execution generating a matching score for each comparison made. For matching with Eigenfinger, the mahattan-based classifier converts the Eigen distance measures into similarity scores. Minutiae and Eigenfinger score-level fusion is then performed to attain the final result. Two databases A (with 86 individuals and 443 samples) and B (with 31 individuals and 63hand images) were used. The processing time performance recorded for minutiae matching experiments was approximately 29-59 milliseconds (ms) per comparison, which resulted in a total average processing of about between 2478 - 5225 ms per identification. For Eigenfinger processing, it was reported to take about less than 1 millisecond (ms). A great recognition performance improvement was observed in multi-instance experiments than in the unimodal experiments. With minutiae experiments Equal Error Rates (EER) of 0.21% and 0.00% for database A and B were obtained respectively, while EER of 1.45% and 1.48% for database A and B were obtained respectively in the Eigenfinger experiments.

2.1.1 PATTERN-BASED MATCHING TECHNIQUES

In the pattern-based matching methods, the fingerprint image samples are acquired/captured and their templates stored in a database. Matching then follows by comparing the basic fingerprint patterns such as the arch, whorl, delta and loop; between the previously stored template and a candidate fingerprint. To achieve a desired output, it requires that the images be aligned in the same orientation. For this to happen, the algorithm has to find a central point in the fingerprint image and focus on that. The stored template contains the type, size, and orientation of patterns within the aligned fingerprint image. During matching, the candidate fingerprint image is graphically compared with the template to determine the degree to which both of them match and a match score is generated [2, 3, 4].

In their 2011 research, Mane et al [33] combined matching scores generated from multiple instances of the same finger acquired using the same fingerprint sensor. They used the score level fusion technique to attain a final recognition accuracy. The FVC2000 DB1, FVC2002 DB1, FVC2004 DB1 and their own BAMU (with 660x4 images) databases where used. They use the pattern-based matching method where a reference point and region of interest are first determined. Matching then follows after filtering the region of interest and computing the average absolute deviation (AAD). Their results show that there was a greater improvement in the recognition accuracy when multiple enrollment was applied than in single enrollment. Equal Error Rates (EER) of 13.7%, 12.0%, 44.5% and 3.00%, where obtained respectively as per the databases listed above.

III. SUMMARY OF PERFORMANCE OVERVIEW, A COMPARATIVE ASSESSMENT OF THE SURVEYED APPROACHES, CHALLENGES AND RECOMMENDATIONS

This section gives a summary of the performance of the different multiple enrollment techniques surveyed, a comparative assessment of the different approaches (techniques) and finally discusses some of the challenges identified and provides recommendations.

TABLE II: SUMMARY OF PERFORMANCE OVERVIEW

Researcher(s)	**Matching Technique(s)**	**Size of Dataset(s)**	**Execution Time & memory used**	**Performance/recognition accuracy**
Lee, Choi, Lee and Kim(2004)	Minutiae-based technique	63 (20 samples each)	Not Reported	Not Reported
Umut, Ross and Jain(2004)	Minutiae-based technique with 2 methods, DEND and MDIST	50 (200 samples each)	Not Reported	DEND-EER (7.3%) and MDIST-EER (6.31%)
Chunyu and Zhou(2006)	Minutiae-based technique	THU-827 (8 samples each), FVC2002 DB1-110, and FVC2002 DB2-110	Not Reported	Overall FRR (0.0907) and FAR (7.97e-5)
Chunxiao, Yin, Jun, and Yang (2009)	Minutiae-based technique	FVC2000 DB1-110, FVC2000 DB2-110, FVC2002 DB2- 110 and FVC2002 DB3-110	Not Reported	EER (2.25%)
Andres and Peter (2009)	Minutia-based technique and Eigenfinger	A-86 (443 samples), B-31 (63 images)	Minutiae-based (between 2478 - 5225 ms per identification) and Eigenfinger (less than 1 millisecond (ms))	Minutiae-based (A-EER (0.21%) and B-EER (0.00%)), Eigenfinger (A-EER (1.45%) and B-EER (1.48%))
Mane, Arjun V., Yogesh S. Rode, and K. V. Kale.(2011)	Pattern-based technique	FVC2000 DB1-110, FVC2002 DB1-110, FVC2004 DB1-110, and BAMU-660 (4samples each)	Not Reported	FVC2000 DB1-EER (13.7%), FVC2002 DB1-EER (12.0%), FVC2004 DB1-EER (44.5%), and BAMU-EER (3.00%)

3.2 A COMPARATIVE ASSESSMENT OF THE DIFFERENT APPROACHES

In this section, we discuss a general comparison in terms of performance amongst the different approaches surveyed basing on the categories of classifications and the recognition performance rates.

Looking at the different categorizations; minutiae-based matching techniques and pattern-based matching techniques, and basing on the summary of the performance rates under each, that is; for minutiae-based matching techniques, we have, 7.3%&6.31%, 0.0907%&7.97e-5%, 2.25%, 0.21%&0.00%, 1.45%&1.48%, and, for pattern-based matching techniques, we have, 13.7%, 12.0%, 44.5%, and 3.00%, we make a comparison. From the above summaries, we notice that even though, there was some good accuracy rate of EER 3.00% in the pattern-based matching techniques, minutiae-based techniques exhibited better performances. This would imply that, multiple enrollment for fingerprint recognition using minutiae-based techniques can perform better than the pattern based techniques. However, in our analysis, we have found only one research work that carried out multiple enrollment for fingerprint recognition using the pattern-based technique. A conclusive remark therefore about which technique outweighs the other can only be made when more multiple enrollment experiments using pattern-based matching techniques are carried out. We also noted that amongst all the surveyed papers, one which reported almost the best recognition performance rates of 0.21%, 0.00%, 1.45% and 1.48% was based on relatively small sized databases, which could be considered less representative. This therefore implies that using a reasonably large database would be a good basis to make better conclusions. Also, the venture into combining the two commonly used matching methods while using multiple enrollment for fingerprint recognition has not been given attention. Our assumption is that the recognition performance would greatly improve than basing on only one, although the execution time and memory consumption might be of concern. Finally, we also noticed that amongst all the surveyed papers, only one researcher reported the execution time taken and no research reported the memory consumption during the experimentations. However good the recognition accuracy may be in multiple enrollment based fingerprint recognition systems, the execution time (aka speed) and memory consumption still remain a concern in the real world implementation. It is therefore important to address the two parameters to have reliable multiple enrollment based fingerprint recognition systems.

3.3 RESEARCH CHALLENGES IDENTIFIED AND RECOMMENDATIONS

To enrich the understanding of the state of art of multiple enrollment for fingerprint recognition, it is important to know the challenges. We have done an overall sampling, identified some of the crucial challenges as well as provided some recommendations.

One of the challenges cutting across was that local ridges of a fingerprint cannot be entirely categorised by minutiae [21]. This means that minutiae-based matching techniques do not utilize all the unique information exhibited in the ridge structure of fingerprints. In the same research, it was also realised that minutiae-based matching techniques are inferior in matching two or more fingerprint impressions with different numbers of unregistered minutiae points. In this case, pattern-based matching techniques would be sufficient in alleviating such problems since they capture both local and global features of fingerprints [44].

There is still a perception that its only identification systems which should take into account both accuracy and speed since they have to explore the whole database to establish an identity. Verification systems have often focused on accuracy since it is easy to meet response time because of the one-to-one comparisons. We have realized that many researchers in our survey have not considered execution time (aka speed) as an important issue yet multiple enrollment based fingerprint recognition systems perform a lot of many-to-many comparisons. With speed issues, user specific weights could help where by low weights are assigned to those images that are of poor quality and high weights to images with good quality based on certain parameters. With time these weights can be learnt and only considered during the multiple matching basing on a specific request set by the user. It is not only the recognition performance that would improve, but the matching speed as well reduction in memory consumption.

From our analysis, it would also be important to further investigate under what conditions the recognition performance improvements provided by the multiple enrollment fingerprint recognition systems could justify the increase in system cost and user co-operation.

IV. OVERALL ANALYSIS AND FUTURE WORK

In this section, an overall analysis of the survey is done, providing the research gaps and way forward.

A lot of research that has been done relating to multiple enrollment has mainly focused on combining multiple fingerprint matchers (algorithms), like in [52], [28], [53], [31], [54], [21], and in some cases combining multiple fingerprint sensors, like in [29] to achieve better recognition accuracy; rather than concentrating on single fingerprint matchers focusing on multiple enrollment of fingerprints. Others like [30], [18], [16], [55], [17], [15], [19], and [20], have focused on fusion of multiple sources of information to improve recognition performance. From the analysis of the previously done research related to multiple enrollment, some of the researchers have implemented decision level fusion in fingerprint verification; whereas the majority have implemented score level fusion and others have tried to combine the two in some cases. From the literature searched, it is evident that there is a lot of interest in combining multiple sources of biometric information to improve the recognition accuracy.

However, on top of the avenues for improving recognition accuracy, little research has concretely concentrated on improving the matching speed (execution time) of such multiple source based biometric systems, the usability, memory consumption as well as acceptability. Although multi-modal, multi-sensor, multi-matcher/algorithm based fingerprint recognition system can improve the recognition performance, their implementation, usability, memory consumption and acceptability in real-world deployment situations may not easily be achieved; it would require more costs to acquire the necessary extra resources, to implement as well as convincing and training users to adapt to them. The analyzed recognition accuracies from the current researches are also still low. Also according to our analysis, researchers have not concretely recommended which fingerprint matching methods work best when multiple enrollment is deployed in real world scenarios.

4.1 FUTURE WORK

The analysis and gaps presented in the section above spur new research directions in the area of multiple enrollment for fingerprint recognition. Future work would take a closer study on the existing fingerprint biometric systems that use multiple sources of biometric information (concentrating mainly on multiple samples of fingerprints from many fingers of the same individual) to evaluate their performance (recognition accuracy), matching speed, acceptability, usability, and memory consumption.

This future research study would aim at proposing a novel multiple enrollment fingerprint recognition approach which would further improve recognition accuracy, the matching speed and reduce memory consumption in multiple enrollment based fingerprint recognition systems. This approach would also focus on performance and accuracy evaluation of both minutiae-based and pattern-based fingerprint matching methods to realize which method performs better when multiple enrollment is deployed. Rather than using multiple matchers, multiple modals, or multiple sensors; a single matcher, sensor and modal would be used to allow for acceptability, usability and easier implementation.

V. CONCLUSIONS

In this survey, developments in multiple enrollment for fingerprint recognition technology over the past twenty years has been presented, hoping to give a comprehensive account of the state of the art in the field. It can be concluded from the comparative assessment of the different approaches that, the performance of multiple enrollment fingerprint recognition systems has continuously improved with a lot of technology advancements over the years.

At the same time, approaches for implementing multiple enrollment for fingerprint recognition are more diversified compared with the situation in the 20th century, with minutiae-based matching techniques generally giving a better recognition accuracy, but being more inferior in matching two or more fingerprint impressions with different numbers of unregistered minutiae points, as well as not being able to entirely categorize local ridges of a fingerprint. Our analysis has revealed that combining both minutiae and pattern-based matching techniques while deploying multiple enrollment would have a significant influence on the recognition result, but devising a fast algorithm to ameliorate the time consuming computation and memory consumption is a pre-requisite for such multiple enrollment fingerprint recognition systems to gain real world implementation and commercial popularity.

At the moment, the lack of taking into account the computation time and memory consumption visa-vee recognition accuracy is one of the challenges facing multiple enrollment recognition systems; papers include experimental results that are based mainly on accuracy. Also, not every paper states explicitly under what conditions the recognition performance improvements provided by the multiple enrollment fingerprint recognition systems could justify the increase in system cost and user co-operation, making a thorough comparison impractical and obstructing identification of the best approach.

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